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Description: Research Article

A manufacturing system energy-efficient optimisation model for maintenance-production workforce size determination using integrated fuzzy logic and quality function deployment approach

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Abstract

In maintenance systems, the current approach to workforce analysis entails the utilisation of metrics that focus exclusively on workforce cost and productivity. This method omits the "green" concept, which principally hinges on energy-efficient manufacturing and also ignores the production-maintenance integration. The approach is not accurate and could not be heavily relied upon for sound maintenance decisions. Consequently, a comprehensive, scientifically-motivated, cost-effective and an environmentally-conscious approach are needed. With this in view, a deviation from the traditional approach through employing a combined fuzzy, quality function deployment interacting with three meta-heuristics (colliding bodies optimisation, big-bang big-crunch and particle swarm optimisation) for optimisation is made in the current study. The workforce size parameters are determined by maximising workforce size's earned-valued as well as electric power efficiency maximisation subject to various real-life constraints. The efficacy and robustness of the model is tested with data from an aluminium products manufacturing system operating in a developing country. The results obtained indicate that the proposed colliding bodies' optimisation framework is effective in comparison with other techniques. This implies that the proposed methodology potentially displays tremendous benefit of conserving energy, thus aiding environmental preservation and cost of energy savings. The principal novelty of the paper is the uniquely new method of quantifying the energy savings contributions of the maintenance workforce.

Keywords: Workforce, fuzzy inference system, quality function deployment, colliding bodies optimisation

1. Introduction

The adequate determination of sufficient workforce size for manufacturing concerns has been a problem that has confronted industries for decades. The problem is further compounded when planning for both maintenance and production at the same time as in the case of many small-and medium-scale enterprises (Sahu *et al*., 2013), which are financially incapable to engage multiple employees to independently run both production and maintenance functions at the same time. Instead, industries engage multi-skilled professionals to man both the production and maintenance functions at the same time. The optimal determination of workforce sizes in such a setting, where the same technical personnel (engineers, technicians and factory support staff) run both maintenance and production functions at the same time, is of great interest in manufacturing environments where industrial economy is a priority in achieving competitive status in the market.

Economic workforce size determination is feasible in an environment where uncertainty in both production and maintenance activities could be captured and incorporated into the modelling framework.

Although several studies have attempted to determine the workforce size without due consideration for uncertainty (Techawiboonwong *et al*., 2006; Yue *et al*., 2007; Ighravwe and Oke, 2014), decisions made from such models are often of significant shortcomings and sometimes wrong. Due to the progressive development in literature and at the same time the great success attached to fuzzy logic applications in practice, there is an economic significance and management importance in quantifying workforce parameters in manners to incorporate variations in uncertainty, evidenced in maintenance and production workforce functions in order to make correct decisions. Although substantial works have been done to quantify or determine workforce size in the past (Felan and Fry, 2001; Yue *et al*., 2007; Fletcher *et al*., 2008; Ighravwe and Oke, 2014), from the review of literature, it can be asserted that most of the workdone have been restricted to service settings such as hospitals, while production optimisations in manufacturing have gained little attention of researchers. Furthermore, maintenance settings have attracted lesser attention of investigators and the integrated maintenance and production workforce determination has received the least attention in research.

Owing to the important role that manufacturing operations plays in today's manufacturing system, a great need arises to capture all possible outcomes of workforce variables in both production and maintenance systems. Consequently, the current article describes the development of an integrated fuzzy logic and quality deployment model (QFD) and their use to determine the workforce variables for both maintenance and production systems. The workforce values resulting from the current work are intended for use by industries in general to improve the quality of decisions in manufacturing systems.

In determining the workforce size for a manufacturing outlet in which energy efficiency is critical and the production-maintenance services are performed by the same set of personnel, an adequate understanding of all factors affecting the workforce estimation is needed. Generally, the development of workforce size models should be based on qualitative measures such as workforce fatigue and training impacts as well as quantitative measures such as productivity, efficiency, utilisation and turnover rate. The data specifically related to quantitative measures are obtainable from field visits and questionnaire administration. Also, questionnaires designed to obtain the opinions of company management could provide substantial data on the qualitative aspects of the data. Since diverse personnel responses are obtainable, it is sensible to conduct an evaluation and analysis of the workforce size in a fuzzy environment. It means that the company management are able to express their minds on workforce issues in a range of linguistic variables over a fuzzy scale based on their own subjective opinions. Thus, the translation of the managers' verbal expressions into numeric values with fuzzy models could be allowed (El-Baz, 2011).

Consequently, the current paper suggests a novel combined integration of fuzzy inference systems and QFD. This integrated framework is potentially capable of tracking the rating problem quantitatively and also the qualitative factors involved in workforce size determination and effectively analyse the scenario. The method advanced in the current paper yielded an analysis of the workforce needed for the sub-units within the production and maintenance systems. To further explore the possibility of using improved optimisation algorithm for maintenance variable optimisation, the article selects colliding bodies' optimisation (CBO) algorithm as a new solution method for the proposed model.

Judging by the best of the authors' knowledge, no study has applied CBO in maintenance variables optimisation for workforce size determination. However, it is interesting to apply new meta-heuristics that have been proven successful in other environments to expand the application frontiers of such a meta-heuristic and improve performance. The performance of CBO and particle swarm optimisation (PSO) has been investigated, and a superior performance of CBO was observed (Kaveh and Mahdavi, 2014a, b). In carrying out the literature study for the current work, one was confronted with the problem of relevance and appropriate capture of literature as to the identification of the most appropriate literature to the research being contributed. The most relevant literature falls in the categories of workforce planning literature and those papers written using the integrated fuzzy and QFD concepts are the most appropriate. From another perspective, enquires were directed to probing the literature concerning the marriage of production functions and maintenance activities. A brief literature review then follows:

The fuzzy multiple-objective programming technique contributed by Karsak (2004) has the capability to contain subjective as well as imprecise information that is characteristically present in the planning process of QFD used to evaluate the satisfactory level of design requirements. The author applied linguistic variables to depict the design data that is imprecise as well as the degree of importance of every design goal. The model was implemented using a real-life application. Yan and Ma (2015) contributed a decision-making method to concurrently treat the problem of uncertainties solved with the use of QFD. The developed model is two-phased and solves two classes of uncertainties. The first level relates to the determination of the frizzy preference association of various DRs in terms of every customer, which depends on the order-based semantics pertaining to linguistic information. Furthermore, the second level; involves the determination of the prioritization of DRs using synthesis of every customer's fuzzy preference association into a total one by fuzzy majority. Applicability of the approach was illustrated with two principal illustrations involving a Chinese-based restaurant as well as a manufacturing industry that operates on flexible principle.

Zandi and Tavana (2011) contributed a structured approach to assess and pick the most acceptable agile e-CRM structure in a fast-changing production environment. The basis for evaluating the e-CRM frameworks is customer as well as financial-based features to obtain manufacturing agility. The work prioritized then e-CRM structures in line with their financial-based attributes with the use of frizzy group real-options computational model. Furthermore, the e-CRM framework categorized in terms of their customer-based behavior with the use of hybrid frizzy-group permutation as well as a four-stage fuzzy-QFD approach in terms of three principal outlooks of agile manufacturing (i.e. operational, functional and strategic agilities). On a final note, the most attractive agile e-CRM structure was picked with the use of Technique for Order of Preference by Similarly to Ideal Solution (TOPSIS) approach. Using case study analysis, the feasibility of applying the proposed approach was demonstrated and the procedural and algorithmic efficacy of the approach was displayed.

Jin and Bai (2011) proposed a method for developing manufacturing strategy from the perspective of quality function deployment. The contribution as well as fused frizzy set-theory with the house-of-quality to present an organized tool to track the characteristics imprecision as well as vagueness of decisions. The intention is to aid the smooth analysis of decision-related QFD information. An illustration was made using a case study to demonstrate the usefulness of the method. Bottani (2009) contributed a method that links agile enablers to agile attributes as well as competitive basis. The focus of the work was to pin-point the most relevant enablers to be used by organizations staring from competitive characteristics inherent in the related market. The method is dependent on the QFD philosophy (i.e. the house-of-quality), which has explored frizzy logic in translating linguistic information needed for associations and correlation matrices with numerical data using information from literature. Vinodh and Sureshkumar (2011) reported the fusion of frizzy logic with the QFD structure and carried out a case study oriented on a manufacturing system operating on electronics switches production in India. The above literature, primarily on the integration of QFD as well as frizzy logic, has been restricted to design, restaurant planning, flexible manufacturing system and agile manufacturing. To the best of our knowledge, the literature is deficient in studies of integrated frizzy logic and QFD applied to workforce size determination.

Next, a brief account of studies on workforce planning is given. A study that investigated the problem of production's permanent and temporary workforce as well as inventory cost minimisation was reported by Techawiboonwong *et al*. (2006). The ratios of full-time and part-time workers as well as the skill requirements for each work-station were considered. The need to retain workers with flexible skill sets was studied by Felan and Fry (2001) and it was observed that the use of non-flexible workforce has negative impact on the performance of production systems. Yue *et al.* (2007) pointed out that to increase workers' flexibility, adequate provisions should be made for learning in a system. Fletcher *et al*. (2008) considered the problem of correlation of workers' attitudes and production cycle time in production systems. The result from Fletcher *et al*. (2008)'s study revealed that production task performance variations of production workers were not influenced significantly by their attitudes.

From the above discussions, the workforce planning literature has not considered the use of QFD-based model that accounts for the size of workforce if the same team will be used for both production and maintenance functions. The remaining structure of this study are organised as follows: Section 2 contains a brief review of manufacturing sustainability and optimisation. In section 3, the proposed optimisation model is presented and the three selected meta-heuristics are discussed in section 4. Sections 5 and 6 contain the proposed model application and the discussion of results, respectively. The conclusions of this study are in section 7.

2. Manufacturing sustainability and optimisation

2.1 Manufacturing energy efficient for sustainability

Globally, manufacturing industries have been acknowledged as indispensable from the viewpoint of economy, provision of tangible goods for consumers, employment provision, corporate social responsibility services and economic strength (Duflon *et al*., 2012). However, energy efficiency leading to sustainability, in manufacturing is one practice that has gained the attention of manufacturers and researchers. Energy efficiency boasts the economic and technical of performance environmentally-friendly and socially-responsible systems (Faulkner and Badurdeen, 2014). In contemporary times, manufacturing is expected to respond positively in a proactive manner to tackle the significant challenges possed by the environment towards sustainability through energy programmes. This calls for aggressive efforts at exploiting every opportunity in the manufacturing enterprise towards more efficient usage of energy, including the electrical power, which primarily drives manufacturing (Dauflon *et al*., 2012). However, this could not be treated in isolation since optimisation of energy utilisation models will give local optimal results. There must be a concerted effort in integrating factors such as workforce sizing into the modelling framework of energy utilisation.

Apart, the special case of the production-maintenance functional integration should be incorporated into the model. Since conservation of energy promotes the economic soundness of industries, a natural starting point is to develop models that quantify, monitors and control the industrial economy efficiently and link then to workforce variables in manufacturing systems. Till date, no such models exist and efforts to integrate such models when considering the same personnel to run both the production system and the maintenance function have not been documented in literature.

2.2 Manufacturing system optimisation

Optimisation of system or process parameters is an important stage in workforce size determination, particularly when an integrated production and maintenance system is considered. Certainly, the work-study approach and the job evaluation analysis are accepted scientific approaches currently being dealt with by human resource practitioners in determining workforce sizes. Unfortunately, these approaches are inappropriate given the level of research and development worldwide, because they do not consider the interrelationships of production and maintenance workforce. These approaches are limited in their inabilities to consider the dynamic skill levels of staff and also inappropriate for the absence of economic considerations such as energy efficiency.

The benefits of workforce size optimisation may not be fully achieved when workforce models that incorporate non-linear relationships are solved with conventional optimisation techniques. This is as a result of convectional optimisation techniques' drawbacks, tendency to be trapped at local optimal solutions. The drive for global optimal solutions has propelled the current work to the application of a novel algorithm, colliding bodies, originally by developed Kaveh and Mahdavi (2014a).

In order to ensure the right size of personnel and to reduce the overall workforce effectiveness, it is necessary to select the optimal workforce sizing parameters. The colliding bodies algorithm, based on the principle of momentum and energy will be used for the optimisation of the workforce sizing conditions in manufacturing systems such that the same workforce is utilised for both maintenance and production. In comparison with the traditional optimisation techniques, the colliding bodies algorithm is robust and attains global solution. The main contributions of this article are: (1) development of an approach for determining the workforce size of a manufacturing system in a case where the same workforce is used for both maintenance and production activities using fuzzy mathematics and QFD; and (2) a practical application of the proposed method in a production company.

3. Methodology

The performance of manufacturing systems can be linked to different factors like cost (salaries), human (workforce size), machine (production volume) and time (production and maintenance) management. The quest for the determination of optimal values for the above mentioned management factors necessitate the use of QFD in this article. This helped in establishing the interrelationships among these factors and workers' group. A framework for determining maintenance-production relationship and the production workforce that is used in evaluating the contribution of each workforce group is presented in Figure 1. The proposed framework is anchored on fuzzy inference system (FIS) and QFD methodologies.

In stage 1, the integration of different factors used in generating an index for a particular aspect of a system evaluation is presented. Since the requirement of accepting a criterion as adequate is relative and often expressed in linguistic terms, this study employed the use of FIS in creating membership functions. Decision makers' opinions are subjective and can sometime lead to incorrect decisions, whose consequences may result in losses of lives, interruptions in company's operations, manpower shortages, loss of company's profits, severe damages to equipment and machineries, and penalty costs. To obtain objective information on workforce, opinion pooling from experts should be used when implementing the framework in Figure 1. In stage 2, grey relational analysis (GRA) system was employed in generating a single index for the system's overall performance, while stage 3 utilises the concept of QFD in determining the contributions of the different workforce groups to organisation goals. Also, stage 3 is where the proposed optimisation model was formulated.

3.1 Nomenclature

The following nomenclature is used in the proposed model.

Indices:	
I	Manufacturing task
J	Workers' group
L	Performance index
T	Sub-planning period
L	Total number of performance indices
M	Total number of manufacturing tasks
N	Total number of workers' group
T	Total planning period
Parameters:	
$\widehat{y}_l$	Minimum value of performance index l
$\breve{y}_l$	Maximum value of performance index l
$\widehat{x}_{ij}$	Minimum number of workers in manufacturing task i belonging to worker's group j
$\breve{x}_{ij}$	Maximum number of workers in manufacturing task i belonging to workers' group j
$¢_{ijt}$	Average unit earned-value of workers in manufacturing task i belonging to workers' group j at period t
Variables	
x_{1jt}	Number of workers scheduled to carry out production assignments only belonging to workers' group j at period t
x_{2jt}	Number of workers scheduled to carry out maintenance-production assignments belonging to workers' group j at period t
w_{1jt}	Amount of workload for a worker's schedule to carry out production assignment belonging to workers' group j at period t
w_{2jt}	Amount for a workload for a worker's schedule to carry out production and maintenance assignments belonging to workers' group j at period t
a_{1jt}	Amount of idle time expected from a schedule to carry out production assignment belonging to workers' group j at period t
a_{2jt}	Amount of idle time expected from a schedule to carry out production and maintenance assignments belonging to workers' group j at period t
y_1	Machine performance index
y_2	Human performance index
y_3	Cost management index
y_4	Time management index

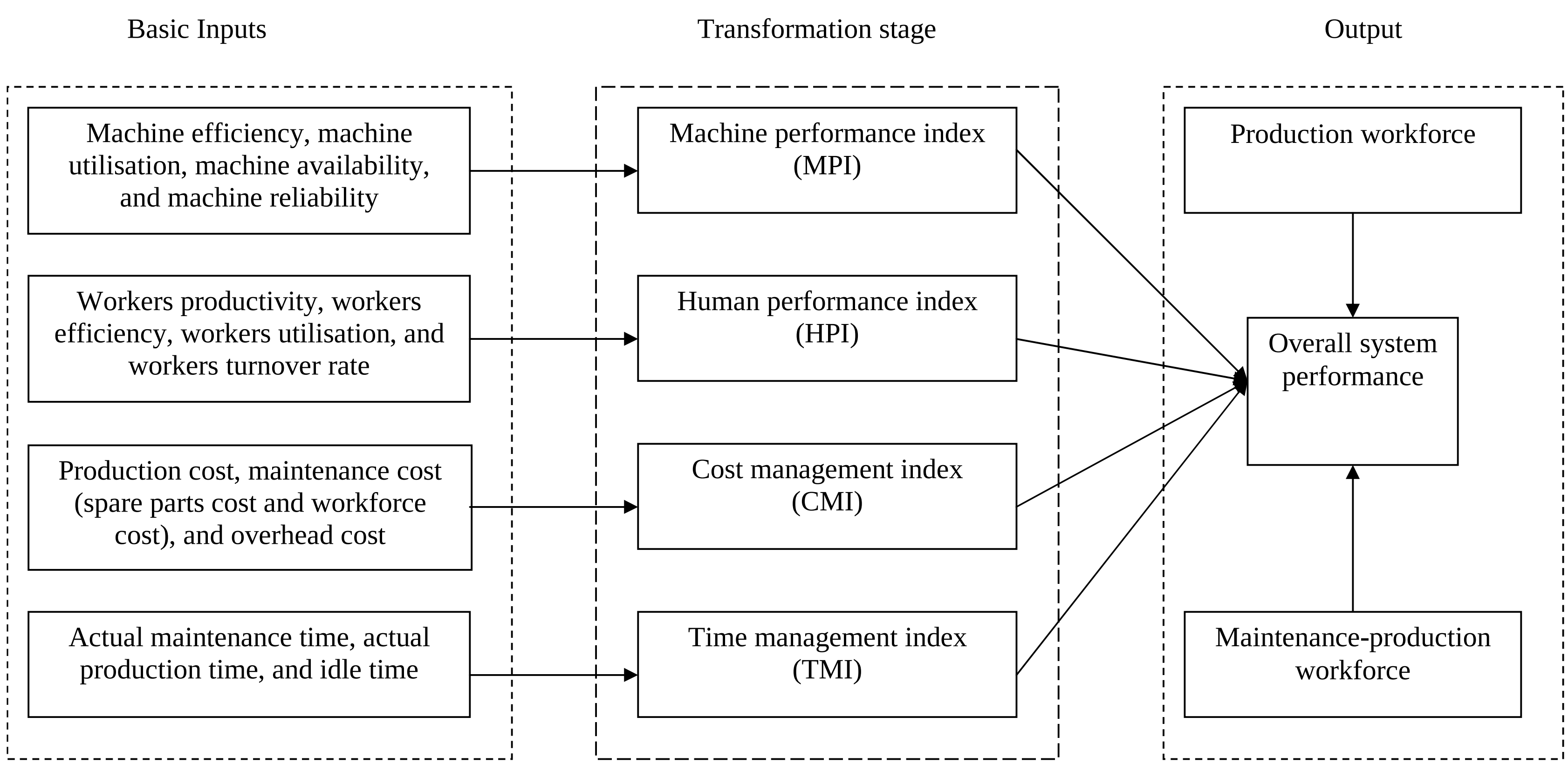


Figure 1: A three-stage framework for maintenance-production workforce determination

3.2 Model development

The optimal value for electric power usage in a production system is affected by wastes that may result from the workforce. One of such wastes is workers being idle when they are supposed to use the available electricity for productive activities (maintenance and production). To be more practicable, a loss function ($\overline{L_i}$) for the amount of electricity supply for a particular manufacturing activity is considered. This function is used to account for the expected losses in energy usage in a system. By combining the allocated and idle times of workers, the electric power efficiency objective function is defined as Equation (1).

$$\text{Max } Z_1 = \sum_{t=1}^{T} \frac{\left(\left[(1+O_{1t})\sum_{j=1}^{N}\left(w_{1jt} - \text{a}_{ijt}\right)x_{1jt} + \sum_{j=1}^{N}\left(w_{1jt} - w_{2jt} - \text{a}_{ijt}\right)x_{2jt}\right] + (1+O_{2t})\sum_{j=1}^{N}\left(w_{2jt} - \text{a}_{ijt}\right)x_{2jt}\right)}{\left(\left(\left[(1+O_{1t})\sum_{j=1}^{N} w_{1jt}x_{1jt} + \sum_{j=1}^{N}\left(w_{1jt} - w_{2jt}\right)x_{2jt}\right] - L_{1t}\right) + \left(\left[(1+O_{2t})\sum_{j=1}^{N} w_{2jt}x_{2jt}\right] - L_{2t}\right)\right)} \tag{1}$$

where, O_{it} is the proportion of overtime time for manufacturing activity i at period t that cannot be easily quantified, and is the amount of electric power consumption per measure of manufacturing activity (time).

The overall system performance index value that a system will obtain from engaging the different scheduled workers at each period is expressed as Equation (2). Since there are no direct interrelationships among the various performance indices, a first-order regression equation is used in estimating the overall system performance index at a particular period *t*.

$$\text{Max } Z_2 = \sum_{t=1}^{T}\left(\sum_{l=1}^{L}\left(a_l y_{lt}\right) + c\right) \tag{2}$$

where a_l and c are constant parameters to be estimated from the regression equation.

The mathematical expressions for y_1, y_2, y_3, and y_4 are given in Equations (3) to (6), respectively. With Equations (3) to (6), the minimum and maximum limits for y_1, y_2, y_3, and y_4 can be determined using simulation. This study selects trapezoidal membership function in converting linguistic terms to crisp values.

$$y_1 = \frac{\text{«}_{ME}(x_{ME}).x_{ME} + \text{«}_{MU}(x_{MU}).x_{MU} + \text{«}_{MA}(x_{MA}).x_{MA} + \text{«}_{MR}(x_{MR}).x_{MR}}{\text{«}_{ME}(x_{ME}) + \text{«}_{MU}(x_{MU}) + \text{«}_{MA}(x_{MA}) + \text{«}_{MR}(x_{MR})} \tag{3}$$

where

$«_{ME}$ and x_{ME} are the membership functions as well as crisp values, respectively, for machine efficiency, $«_{MU}$ and x_{MU} are the membership functions as well as crisp values, respectively, for machine utilisation, $«_{MA}$ and x_{MA} are the membership functions as well as crisp values, respectively, for machine availability, and $«_{MR}$ and x_{MR} are the membership functions as well as crisp values, respectively, for machine reliability,

$$y_2 = \frac{«_{WP}\left(x_{WP}\right).x_{WP} + «_{WE}\left(x_{WE}\right).x_{WE} + «_{WU}\left(x_{WU}\right).x_{WU} + «_{WT}\left(x_{WT}\right).x_{WT}}{«_{WP}\left(x_{WP}\right) + «_{WE}\left(x_{WE}\right) + «_{WU}\left(x_{WU}\right) + «_{WT}\left(x_{WT}\right)} \tag{4}$$

where, $«_{WP}$ and x_{WP} are the membership functions as well as crisp values, respectively, for workers productivity, $«_{WE}$ and x_{WE} are the membership functions as well as crisp values, respectively, for workers efficiency, $«_{WU}$ and x_{WU} are the membership functions as well as crisp values, respectively, for workers utilisation, and $«_{WT}$ and x_{WT} are the membership functions as well as crisp values, respectively, for workers turnover rate.

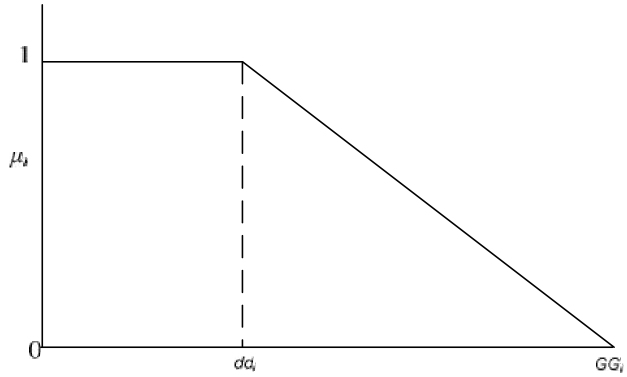
$$y_3 = \frac{«_{PC}\left(x_{PC}\right).x_{PC} + «_{SP}\left(x_{SP}\right).x_{SP} + «_{WC}\left(x_{WC}\right).x_{WC} + «_{OC}\left(x_{OC}\right).x_{OC}}{«_{PC}\left(x_{PC}\right) + «_{SP}\left(x_{SP}\right) + «_{WC}\left(x_{WC}\right) + «_{IC}\left(x_{OC}\right)} \tag{5}$$

where, $«_{PC}$ and x_{PC} are the membership functions as well as crisp values, respectively, for production cost, $«_{SP}$ and x_{SP} are the membership functions and crisp values, respectively, for spare parts costs, $«_{WC}$ and x_{MC} are the membership functions as well as crisp values, respectively, for workforce costs, and $«_{OC}$ and x_{OC} are the membership functions as well as crisp values, respectively, for overhead costs.

$$y_4 = \frac{«_{TM}\left(x_{TM}\right).x_{TM} + «_{TP}\left(x_{TP}\right).x_{TP} + «_{TI}\left(x_{TI}\right).x_{TI}}{«_{WP}\left(x_{WP}\right) + «_{TP}\left(x_{TP}\right) + «_{TI}\left(x_{TI}\right)} \tag{6}$$

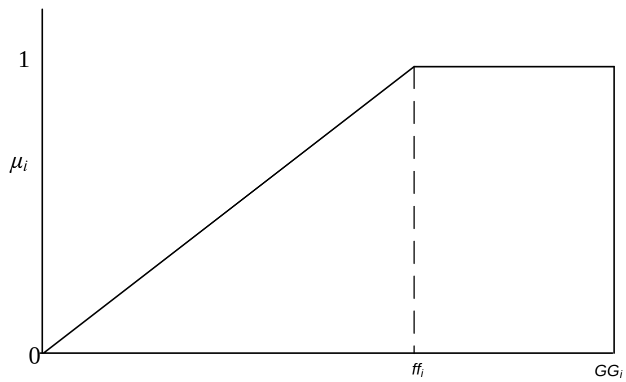
where, $«_{TM}$ and x_{TM} are the membership functions as well as crisp values, respectively, for the actual maintenance time, $«_{TP}$ and x_{TP} are the membership function as well as crisp values, respectively, for the actual production time, and $«_{TI}$ and x_{TI} are the membership functions as well as crisp values, respectively, for idle time.

Based on the questionnaire in Appendix A, the membership functions and the characteristic expressions for the various linguistic terms for the minimum and maximum performance indices (inputs) are shown in Figures 2 and 3, respectively. The values for accepting any inputs as having a membership value of 1 is taken at 95 % of the average values of the total simulated values for any input. The determination of the minimum and maximum values for each of the performance index is evaluated using grey relational analysis (GRA).



$$\text{«}_i = \begin{cases} 1 & \mathrm{G_i} \leq dd_i \\ 1 - \dfrac{dd_i}{GG_i} & \mathrm{G_i} > dd_i \end{cases}$$

Figure 2: Membership functions for the minimum are preferable inputs



$$\text{«}_i = \begin{cases} \dfrac{GG_i}{ff_i} & \mathrm{GG_i} \leq ff_i \\ 1 & ff_i > \mathrm{G_i} \end{cases}$$

Figure 3: Membership functions for the maximum are preferable inputs

where
dd_i is the boundary between partial and complete memberships function for minimum inputs, and
ff_i is the boundary between partial and complete memberships function for maximum inputs.

Since a manufacturing system with low manufacturing costs and operation time is preferable to a manufacturing system with high manufacturing costs and operation time, the normalisation scheme for the results obtained for the costs and time management indices is estimated with Equation (7). For the machine and human performance indices, high values are preferable, that is the higher-the-better, Equation (8) is used as the normalisation scheme for machine and human performance indices (Hasani *et al.*, 2012).

$$x^*(k) = \frac{\max x_i^o(k) - x_i^o(k)}{\max x_i^o(k) - \min x_i^o(k)} \tag{7}$$

$$x^*(k) = \frac{x_i^o(k) - \min x_i^o(k)}{\max x_i^o(k) - \min x_i^o(k)} \tag{8}$$

where, $x_i^o(k)$ connotes the original sequence and $x_i^*(k)$ represents the sequence after data pre-processing

$\min x_i^o(k)$ and $\max x_i^o(k)$ are the minimum and maximum values of $x_i^o(k)$, respectively

The definition of the grey relational coefficient for each of the performance index is expressed with Equation (9).

$$¸_i(k) = \frac{\Delta\min + ¸\Delta\max}{\Delta_{o,i}(k) + ¸\Delta\max} \tag{9}$$

$$\Delta\min = \min_{\forall j \in i} \min_{\forall k} \left\| x_o^*(k) - x_i^*(k) \right\| \tag{10}$$

$$\Delta\max = \max_{\forall j \in i} \max_{\forall k} \left\| x_o^*(k) - x_i^*(k) \right\| \tag{11}$$

where, ¸ is called identification coefficient and its values lie between (0,1). $x_o^*(k)$ and $x_i^*(k)$ are the reference sequence as well as comparative sequence, respectively (Hasani *et al*., 2012).

The grey relational grade (Hasani *et al*., 2012) for the system performance integration is defined with Equation (12).

$$¥_i = \frac{1}{n}\sum_{k=1}^{n} ¸_i(k) \tag{12}$$

The expected optimal values for y_1, y_2, y_3, and y_4 have direct relationships with the total amount of workloads in a production system. The amount of workload in a system for the maintenance-production workers should be close to optimal values, in order to fully enjoy the benefits of optimal values for y_1, y_2, y_3 and y_4. This will enhance the expected earned-value from the maintenance-production workforce. Equation (13) is considered in computing the workforce earned-values.

$$\text{Max } Z_3 = \sum_{t=1}^{T}\sum_{j=1}^{N}\left(¢_{1jt}\left(\left(w_{1jt} - ª_{1jt}\right)x_{1jt} + \left(w_{1jt} - w_{2jt} - ª_{1jt}\right)x_{2jt}\right) + ¢_{2jt}\left(w_{2jt} - ª_{2jt}\right)x_{2jt}\right) \tag{13}$$

The ability of a production system to meet the demand for its products is a function of the proportion of time allocated for production and maintenance activities. In a production system where production workers are assigned to carry on with maintenance activities, the amount of productive time used for production by a worker (x_{2jt}) that carried out maintenance activities will be less than that of a worker (x_{1jt}) who will carry out only production activities only. The implication of this variation in the amount of production time expected from the production workers is that the total amount of products expected from the production system will be less when compared with a situation where production workers are expected to carry out only production activities. The expression for the amount of goods expected from a production system when production workers are scheduled to carry out production and maintenance functions is expressed as Equation (14).

$$r\left(\sum_{j=1}^{N} w_{1jt}x_{1jt} + \sum_{j=1}^{N}\left(w_{1jt} - w_{2jt}\right)x_{2jt}\right) \geq d_t \tag{14}$$

where, d_t is quantity of goods demanded at period t

The interrelationships among the total amount of manufacturing time (W_t), the amount of time spent on production and maintenance tasks as well as the workforce size is used in constraining the quantity of products that will be produced at each period (Equation 15).

$$\sum_{i=1}^{M}\sum_{j=1}^{N} w_{ijt}x_{ijt} \leq W_t \qquad t \in T \tag{15}$$

In order to include uncertainty to the amount of available manufacturing time, we assumed that variation in the total amount of manufacturing time can be handled using the minimum ($W_{\min}$) and the maximum ($W_{\max}$) limits of the available manufacturing time (Equation 16). A similar approach was presented in Mekidiche *et al*. (2013). By applying the concept of uniform distribution constraint (Wu, 2008) and the prescribed confidence or probability level (α), Equations (15) and (16) can be combined to form a single constraint (Equation 17).

$$W_{\min} \leq W_t \leq W_{\max} \qquad t \in T \tag{16}$$

$$\sum_{i=1}^{M}\sum_{j=1}^{N} w_{ijt}x_{ijt} \leq \left(W_{\max} - W_{\min}\right)\left(1 - \alpha\right) + W_{\min} \qquad t \in T \tag{17}$$

By determining the optimal amounts of production and maintenance times, the quantity of electricity supply to power the production systems can be considered as another restrain on the number of production workers in a production system. Given that there is interrelationship between the quantity of electric power required for machineries and workloads in production and maintenance functions at regular and overtime periods, the expected cost for electricity consumption at each period can be estimated as Equation (18).

$$c_t \left(\left[\left(1 + O_{1t}\right)\left(\sum_{j=1}^{N} w_{1jt}x_{1jt} + \sum_{j=1}^{N}\left(w_{1jt} - w_{2jt}\right)x_{2jt}\right)\right] + \left(1 + O_{2t}\right)\sum_{j=1}^{N} w_{2jt}x_{2jt}\right) \leq e_t \quad t \in T \tag{18}$$

where, c_t is the unit cost of electricity at period *t*.

Apart from the time spent for maintenance activities, which affects the production plan, workforce idle time also has an effect on production time management. Given that part of the allocated time for maintenance and production activities is lost to idle activities, it is possible to model the workforce idle time as Equation (19).

$$\sum_{i=1}^{M}\sum_{j=1}^{N} \mathrm{a}_{ij} x_{ij} \leq \left(1-\sim_t\right)\sum_{i=1}^{M}\sum_{j=1}^{N} w_{ij} x_{ijt} \qquad t \in T \tag{19}$$

where, $\sim_t$ is the proportion of the total manufacturing time that all workers are expected to be busy at period *t*.

To determine the contribution value of each worker's group, this study proposes the use of QFD as a means of estimating the importance of each worker's group with respect to the particular performance indices in Figure 1. The designed house of quality for the workers' importance is shown in Figure 4. Based on the knowledge gained from the works of Chin *et al*. (2002), Wang (2007) and Bottani (2009), the HOQ for maintenance-production workforce (Figure 4) implementation is described as follows:

Step 1: Identification of the management requirements (customer requirements) expected from maintenance-production workers. In this study, these requirements have been briefly grouped into four, Figure 1;

Step 2: Classification of workers required into groups (technical requirements) to execute the maintenance and production activities in manufacturing systems. In the current study, workers are grouped into full-time and causal workers. Further breakdown may entail the classification of such section-wise (electrical, mechanical, packing, quality control, and production), cadre-wise (foreman, supervisors, and operators), and gender-wise (male and female);

Step 3: Selection of rating scale for technical requirement relationships, management requirement relationships and the interrelationships among the workers and management requirements. Ranking scale between the workers and management requirements may be expressed as being strong, medium and weak (Bottani *et al*., 2009; Ramanathan and Yunfeng, 2009). These linguistic expressions for scale can be converted to crisp values using direct conversions of 1, 3, 9 (Ramanathan and Yunfeng, 2009) or fuzzy logic approach (Bottani *et al*., 2009);

Step 4: Pair-wise comparison of workers requirements and determination of the degree of importance of each management requirement;

Step 5: Pair-wise comparison of workers and management requirements; and

Step 6: Determination of the absolute and relative importance of each worker's requirement.

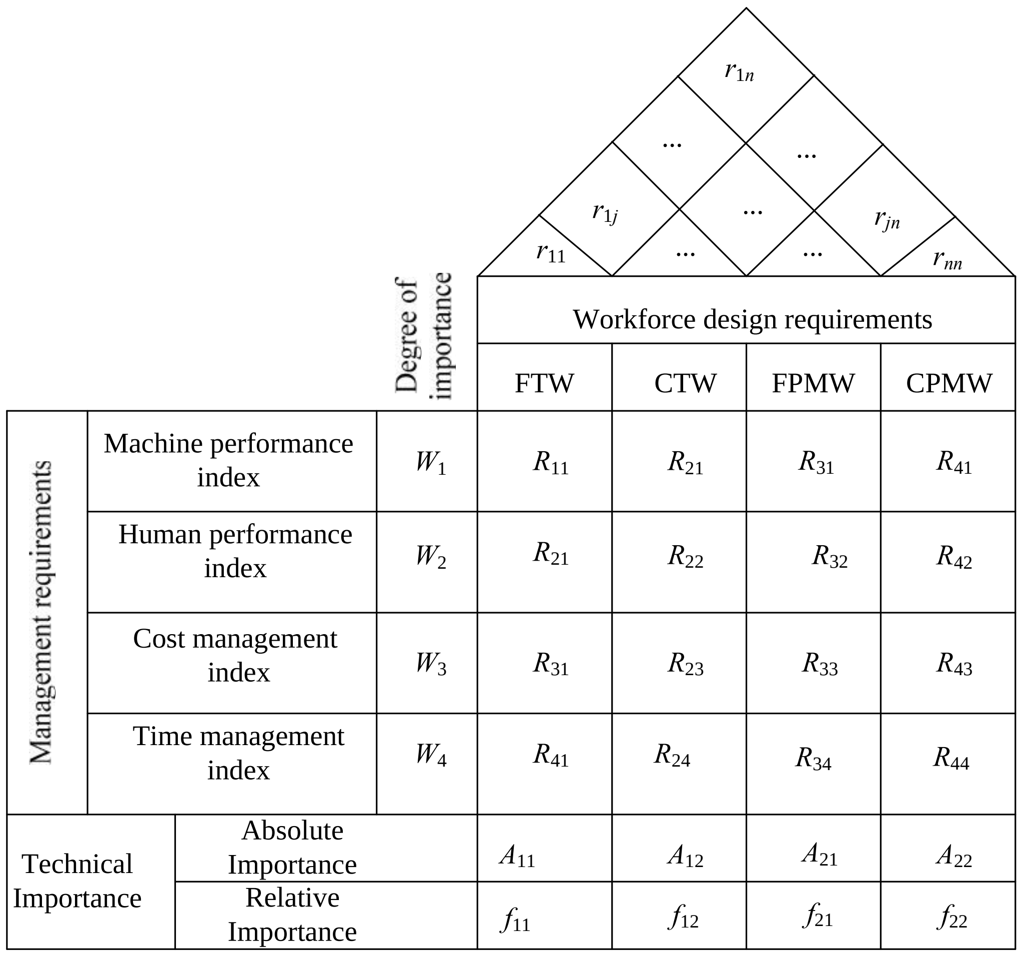


Figure 4: House of quality (HOQ) for workforce relative importance

where
FTW and PTW represent the full-time and causal production workers in a system, respectively, and
FPMW and CPMW represent the full-time and causal maintenance-production workers in a system, respectively.

In this study, the relative importance of each worker's group is estimated with Equation (20). For the current study, $I = J = 2$.

$$f_{ij} = A_{ij} \Big/ \sum_{i=1}^{I} \sum_{j=1}^{J} A_{ij} \tag{20}$$

where I and J are the total number of maintenance section and workers' group, respectively

The ability to meet the production target each period is directly associated with how well y_1 and y_2 are met. By desiring higher for y_1 and y_2, its possible to attain a higher value for production target and vice-versa. The constraint for the limits on y_1 and y_2 is expressed as Equation (21).

$$\breve{y}_l\left(\frac{\sum_{i=1}^{M}\sum_{j=1}^{N}\bar{f}_{ijl}x_{ijt}}{\sum_{i=1}^{M}\sum_{j=1}^{N}\bar{f}_{ijl}x_{ijt,\max}}\right) \geq y_{lt} \qquad l \in 1,2; t \in T \tag{21}$$

The interest of decision makers in production is to reduce the amount of funds and time spent on manufacturing activities. To achieve this objective, constraint (Equation 22) is considered.

$$\breve{y}_l\left(\frac{\sum_{i=1}^{M}\sum_{j=1}^{N}\bar{f}_{ijl}x_{ijt}}{\sum_{i=1}^{M}\sum_{j=1}^{N}\bar{f}_{ijl}x_{ijt,\max}}\right) \leq y_{lt} \qquad l = 3,4; t \in T \tag{22}$$

where $\bar{f}_{ijl}$ is the individual contribution due to manufacturing task *i* expected from workers' group *j* for performance index *l*.

To sustain a particular limit of the production system performance evaluation matrix, limits on each of the performance evaluation index are considered and expressed as Equation (23).

$$\widehat{y}_l \leq y_{lt} \leq \breve{y}_l \qquad l \in 1,2,3,4; t \in T \tag{23}$$

The constraint on each of the worker's group limits is defined with Equation (24), while the expected value for their idle times is restrained with Equation (25).

$$\widehat{x}_{ijt} \leq x_{ijt} \leq \breve{x}_{ijt} \qquad i \in M; j \in N; t \in T \tag{24}$$

$$\widehat{a}_{ijt} \leq a_{ijt} \leq \breve{a}_{ijt} \qquad i \in M; j \in N; t \in T \tag{25}$$

In order to improve the practical application of the proposed model, the shortest normalised distance concept is used in formulating a single objective function as Equation (26). The Pareto solution to the problem is taken as the solution with the least normalised distance (Wu, 2008).

$$D_j = \sqrt{\sum_{i=1}^{3}\left(\frac{Z_i\left(X_j\right)-Z_{i,\min}}{Z_{i,\max}-Z_{i,\min}}S - Z_i^*\right)^2} \qquad (26)$$

where,
S is a scale that ranges between (0,1) and (0-100)
Z_i^* is the ideal solution for objective function i
$Z_{i,\max}$ and $Z_{i,\min}$ are the maximum and minimum values for objective function i in a population at a particular iteration step

The final structure of the non-linear workforce optimisation model is presented as follows:

$$\text{Min } \; D_j = \sqrt{\sum_{i=1}^{3}\left(\frac{Z_i\left(X_j\right)-Z_{i,\min}}{Z_{i,\max}-Z_{i,\min}}S - Z_i^*\right)^2}$$

Subject to:

$$r\left(\sum_{j=1}^{N} w_{1jt}x_{1jt} + \sum_{j=1}^{N}\left(w_{1jt}-w_{2jt}\right)x_{2jt}\right) \geq d_t \qquad t \in T$$

$$\sum_{i=1}^{M}\sum_{j=1}^{N} w_{ijt}x_{ijt} \leq \left(W_{\max}-W_{\min}\right)\left(1-\tilde{\sim}\right)+W_{\min} \qquad t \in T$$

$$c_t \;\left(\left[\left(1+O_1\right)\left(\sum_{j=1}^{N} w_{1jt}x_{1jt} + \sum_{j=1}^{N}\left(w_{1jt}-w_{2jt}\right)x_{2jt}\right)\right]+\left(1+O_2\right)\sum_{j=1}^{N} w_{2jt}x_{2jt}\right) \leq e_t \qquad t \in T$$

$$\sum_{i=1}^{M}\sum_{j=1}^{N} \mathrm{a}_{ijt}x_{ij} \leq \left(1-\sim_t\right)\sum_{i=1}^{M}\sum_{j=1}^{N} w_{ij}x_{ijt} \qquad t \in T$$

$$\sum_{j=1}^{N} x_{ijt} = \sum_{j=1}^{N} f_{ij}\sum_{i=1}^{M}\sum_{j=1}^{N} x_{ijt} \qquad i \in M; t \in T$$

$$\breve{y}_l\left(\frac{\sum_{i=1}^{M}\sum_{j=1}^{N}\bar{f}_{ijl}x_{ijt}}{\sum_{i=1}^{M}\sum_{j=1}^{N}\bar{f}_{ijl}x_{ijt,\max}}\right) \geq y_{lt} \qquad l \in 1,2; t \in T$$

$$\breve{y}_l\left(\frac{\sum_{i=1}^{M}\sum_{j=1}^{N}\bar{f}_{ijl}x_{ijt}}{\sum_{i=1}^{M}\sum_{j=1}^{N}\bar{f}_{ijl}x_{ijt,\max}}\right) \leq y_{lt} \qquad l = 3,4; t \in T$$

$$\overset{\frown}{y}_l \leq y_{lt} \leq \breve{y}_l \qquad i \in n; t \in T$$

$$\overset{\frown}{x} \leq x_{ijt} \leq \breve{x} \qquad i \in M; j \in N; t \in T$$

$$\overset{\frown}{a} \leq a_{ijt} \leq \breve{a} \qquad i \in M; j \in N; t \in T$$

4. Solution Approaches

In this article, three solution methods are considered for the proposed model. The selection of the solution method is based on their unique features.

4.1 Meta-heuristics

Meta-heuristics are algorithms that have gained wide acceptable among researchers and industrial practitioners in the field of systems optimisation. These algorithms are usually population-based and utilise stochastic search principle in exploiting and exploring the available solution spaces for the decision variables in a problem. Some of the first sets of meta-heuristics are genetic algorithm (Holland, 1975), simulated annealing (Kirkpatrick *et al.*, 1983), particle swarm optimisation (Eberhart and Kennedy, 1995) and differential evolution (Storn and Price, 1997). The quest for improved solution quality and computation time reduction has led to hybrid of some of the above algorithms e.g. adaptive differential evolution with optimal external archive (Zhang and Sanderson, 2009),

Some new meta-heuristics in literature are the big-bang big-crunch (Erol and Eksin, 2006), firefly algorithm (Yang, 2009), teaching-learning-based optimisation (Rao *et al.*, 2011) and colliding bodies optimisation (Kaveh and Mahdavi, 2014a). One common feature in meta-heuristic algorithms is the random generation of initial values for the decision variables in a problem, and this is often achieved with Equation (27).

$$x_{ij} = x_{i,\min} + rand\left(x_{i,\max} + x_{i,\min}\right) \tag{27}$$

When dealing with constrained optimisation problem with either free or non-negative decision variables, the values of the objective function(s) and the level of each constraint violation are used in formulating a penalty function. Penalty function is used in evaluating the fitness of each solution in a population. In this article, the fitness function for each particle (bodies) in a population is evaluated with Equation (28). Equations (29) and (30) are used to compute the violation values for inequality and equality constraints in a problem (Coello, 2002). The three meta-heuristics (colliding bodies optimisation, big-bang big-crunch and particle swarm optimisation**)** considered in this article operate based on the concept of shifting the position of bodies or particles.

$$¤(x)_i = f_i(x) + \sum_{j=1}^{J} P_j^1 G_j + \sum_{J=J+1}^{JJ} P_j^2 H_J \tag{28}$$

$$G_j = Max\left[0, g_j(x)\right]^{-} \tag{29}$$

$$H_J = \left| h_j(x) \right|^{\leftarrow} \tag{30}$$

where, $\leftarrow$ and $\rightarrow$ are constant values and it is taken as 1 or 2.

4.2 Colliding Bodies Optimisation

CBO was developed by Kaveh and Mahdavi (2014) from the laws of momentum and energy during the collision of bodies. The basic principle of CBO algorithm is the determination of bodies velocity before and after collusion as well as the value of the coefficient of restitution at a particular iteration step and their masses. The mass of each body is a function of the quality of its solution relative to other bodies in a population (Kaveh and Mahdavi, 2014). The new positions for bodies in a population are determined using the velocities after collusion and previous positions. A summerised outline of a CBO algorithm is presented as follows.

Step 1: Select the stoppage criterion and population size

Step 2: Generate initial values for the work number for the different groups using Equation (27)

Step 3: Assess the fitness of each body in the population using Equation (28). Arrange the solutions in descending order and divide it into two equal parts (stationary and moving parts) using their masses (Kaveh and Ghazaan, 2014).

Step 4: Compute the masses (m_k) for the population using Equation (31)

$$m_k = \frac{1/f_k}{1 \Big/ \sum_{k=1}^{K} 1/f_i} \tag{31}$$

Step 5: Compute the velocity of the stationary (Equation 32) and moving (Equation 33) body before collusion (v_i).

$$v_i = 0 \qquad i = 1,2,\cdots\frac{n}{2} \tag{32}$$

$$v_i = x_{i-\frac{n}{2}} - x_i \qquad i = \frac{n}{2}+1, \frac{n}{2}+2, \cdots n \tag{33}$$

Step 6: Compute the velocity of the stationary (Equation 34) and moving (Equation 35) after collusion ($v_i^{'}$).

$$v_i^{'} = \frac{\left(m_{i+n/2} + \in m_{i+n/2}\right) v_{i+n/2}}{m_i + m_{i+n/2}} \qquad i = 1,2,\cdots\frac{n}{2} \tag{34}$$

$$v_i^{'} = \frac{\left(m_i - \in m_{i-n/2}\right)v_i}{m_i + m_{i-n/2}} \qquad i = \frac{n}{2}+1, \frac{n}{2}+2, \cdots n \tag{35}$$

where, $\in$ is the coefficient of restitution and it is a function of current iteration step (t_s) and the maximum iteration step (t_{max}). The expression for computing $\in$ is given as Equation (36).

$$\in = 1 - \frac{t_s}{t_{\max}} \tag{36}$$

Step 7: Determine the new position of each stationary (Equation 37) and moving colliding (Equation 38) body in the population.

$$x_i^{t+1} = x_i^t + Rnd \circ v_i^{'} \quad i = 1,2,\cdots \frac{n}{2} \tag{37}$$

$$x_i^{t+1} = x_{i-n/2}^t + Rnd \circ v_i^{'} \quad i = \frac{n}{2}+1, \frac{n}{2}+2, \cdots n \tag{38}$$

where, *Rnd* is a uniform random number that is between (-1,1).

Step 8: Change the stoppage criterion.

4.3 BB BC Algorithm

In this work, the big-bang big-crunch evolutionary algorithm is pursued for analysis in view of its outstanding characteristics. The BB-BC is a search approach that is stochastically driven, and completely mimics the evolution of natural biological species in social behavioural pattern. This idea is brought into the evaluation of data points, considered as particles in analysis. Being solution-based, the BB-BC explores the results from a group of solutions in point of time rather than considering only one item of solution. This powerful attribute of BB-BC gives opportunity to this algorithm in searching the complete problem space and hence have the ability to produce mid-point results at any point of time in the event of computation. The success which the big-bang big-crunch (BB-BC) procedure is currently experiencing in literature is due to its low computational time and capacity to generate competitive solutions like other meta-heuristic algorithms (particle swarm optimisation, different evolution and genetic algorithm). The BB-BC procedure is designed after the theory of evolution of the universe and it requires two basic phases. The first phase requires the determination of centre-of-mass for each decision variable in a problem, and this is known as the big-crunch phase. In the second phase, estimation of new positions of particles are known based on the range of the decision variable limits and the associated centre-of-mass, this phase is called the big-bang phase. The description of the BB-BC algorithm is presented as follows (Erol and Eksin, 2006):

Step 1: Select the stoppage criterion and population size
Step 2: Generate initial values for the work number for the different groups using Equation (27)
Step 3: Assess the fitness of each body in the population using Equation (28).
Step 4: Compute the centre-of-mass for each decision variable (m_k), for the population using Equation (39). The value of the global solution can be taken as the centre-of-mass.

$$x_i^c = \frac{\sum_{k=}^{K} x_{ik} / f_k}{\sum_{k=1}^{K} 1/ f_k} \tag{39}$$

Step 5: Determine the new position of each particle in population using Equation (40).

$$x_i^{t+1} = x_i^c + \frac{Rnd_i \left(x_{i,\max} - x_{i,\min} \right) \sim}{t+1} \tag{40}$$

where, Rnd_i is a uniform random number that is between (-1,1), $\sim$ is a constant parameter which controls the search capacity of the algorithm.

Step 6: Change the stoppage criterion.

4.4 Particle Swarm Optimisation

The explorative and exploitative proprieties of PSO algorithm have encouraged its wide applications as one of the mostly-used meta-heuristics for system variable optimisation, especially in the field of electrical engineering. Yet, few reports on the benefits of PSO in maintenance and production activities optimisation are in literature. Worse still, sparse information on the use of PSO algorithm for joint optimisation of maintenance-production variables exist. The PSO algorithm generates global solution for system variables using the concept of cognitive (personal best solution) and social (global solution) knowledge (Eberhart and Kennedy, 1995). The personal best solution is the best value of a particle at after iteration step t, while the global solution is the best value in a population that has been obtained at iteration step t. The combination of the cognitive and social knowledge is used in adjusting the velocity of each particle in a population. A brief explanation of the PSO algorithm is presented as follows (Engelbrecht, 2007):

Step 1: Select the stoppage criterion and population size
Step 2: Generate initial values for the work number for the different groups using Equation (27)
Step 3: Assess the fitness of each particle in the population using Equation (28)
Step 4: Compute the velocity for the population using Equation (41).

$$v_i^{t+1} = wv_i^{t+1} + c_1 r_1 \left(x_i^{pbest} - x_i^t \right) + c_2 r_2 \left(x_i^{gbest} - x_i^t \right) \tag{41}$$

Step 5: Determine the new position of each particle in population using Equations (42)

$$x_i^{t+1} = x_i^t + v_i^{t+1} \quad (42)$$

Step 6: Change the stoppage criterion

5. Model Application

The required number of datasets to demonstrate the applicability of the proposed model is generated through simulation based on the practical data obtained from an aluminium product manufacturing company. The summarised information from the administered questionnaire is presented in Table 1.

Table 1: Practical datasets

Items	Values
Weekly production volume	50 – 70 tonnes
Production cost	₦ 120,000,000 - 150,000,000
Cost of spare parts	₦ 150,000 - 200,000
Overhead cost	₦ 300,000 - 400,000
Production hours	75 hrs
Breakdown time	15 hrs
Production workers idle time	41 – 60 %
Maintenance workers idle time	41 – 60 %
Machine efficiency	61 – 80 %
Machine utilisation	0 – 40 %
Machine availability	61 – 80%
Machine reliability	81 – 100%
Production workers efficiency	61 – 80 %
Maintenance workers utilisation	81 – 100%
Maintenance workers efficiency	61 – 80 %
Production workers utilisation	41 – 60 %
Workers turnover rate	0 – 40 %
Full-time production workers	60-70 workers
Part-time production workers	30-35 workers

By using the simulated data, FIS, and GRA, the results obtained shown for 40 samples are presented in Table 2.

Table 2: Grey relational analysis performance indices

S/n	Data pre-processing				Grey relational coefficient				Grey relational grade
	$x^*(1)$	$x^*(2)$	$x^*(3)$	$x^*(4)$	$\xi_i(1)$	$\xi_i(2)$	$\xi_i(5)$	$\xi_i(4)$	γ_i
1	0.310	0.626	0.910	0.086	0.420	0.572	0.847	0.354	0.548
2	0.191	0.379	0.082	0.317	0.382	0.446	0.353	0.423	0.401
3	0.038	0.585	0.471	0.000	0.342	0.547	0.486	0.333	0.427
4	0.263	0.335	0.870	0.114	0.404	0.429	0.794	0.361	0.497
5	1.000	0.000	0.952	0.263	1.000	0.333	0.912	0.404	0.662

6	0.242	0.533	0.849	0.223	0.397	0.517	0.768	0.392	0.519
7	0.678	0.520	0.098	0.089	0.608	0.510	0.357	0.354	0.457
8	0.545	0.416	0.090	0.328	0.523	0.461	0.355	0.427	0.442
9	0.457	0.102	0.990	0.511	0.479	0.358	0.981	0.506	0.581
10	0.405	0.213	0.348	0.106	0.457	0.389	0.434	0.359	0.409
11	0.683	0.604	0.892	0.618	0.612	0.558	0.822	0.567	0.640
12	0.000	0.552	0.858	0.481	0.333	0.527	0.779	0.491	0.532
13	0.587	0.101	0.944	0.297	0.547	0.358	0.900	0.416	0.555
14	0.018	0.222	0.451	0.560	0.338	0.391	0.476	0.532	0.434

Table 2 (cont'd): Grey relational analysis performance indices

S/n	Data pre-processing				Grey relational coefficient				Grey relational grade
	$x^*(1)$	$x^*(2)$	$x^*(3)$	$x^*(4)$	$\xi_i(1)$	$\xi_i(2)$	$\xi_i(5)$	$\xi_i(4)$	γ_i
15	0.528	0.387	0.956	0.499	0.514	0.449	0.920	0.500	0.596
16	0.210	1.000	0.951	0.898	0.388	1.000	0.910	0.830	0.782*
17	0.364	0.437	0.878	0.075	0.440	0.470	0.804	0.351	0.516
18	0.423	0.801	0.564	0.137	0.464	0.715	0.534	0.367	0.520
19	0.611	0.671	0.490	0.619	0.562	0.603	0.495	0.567	0.557
20	0.197	0.701	0.559	0.637	0.384	0.626	0.532	0.579	0.530
21	0.263	0.636	0.959	0.607	0.404	0.579	0.924	0.560	0.617
22	0.419	0.512	0.920	0.452	0.463	0.506	0.863	0.477	0.577
23	0.328	0.661	0.000	0.240	0.427	0.596	0.333	0.397	0.438
24	0.237	0.480	1.000	0.287	0.396	0.490	1.000	0.412	0.575
25	0.264	0.286	0.962	0.033	0.404	0.412	0.929	0.341	0.522
26	0.390	0.550	0.911	0.098	0.451	0.526	0.850	0.357	0.546
27	0.555	0.550	0.497	0.362	0.529	0.526	0.498	0.439	0.498
28	0.355	0.602	0.969	0.771	0.437	0.557	0.942	0.686	0.655
29	0.169	0.520	0.929	0.868	0.376	0.510	0.876	0.792	0.638
30	0.079	0.670	0.637	0.386	0.352	0.603	0.579	0.449	0.496
31	0.143	0.055	0.714	0.273	0.369	0.346	0.636	0.408	0.440
32	0.169	0.445	0.991	0.256	0.376	0.474	0.982	0.402	0.558
33	0.228	0.169	0.974	0.787	0.393	0.376	0.951	0.702	0.605
34	0.284	0.457	0.124	0.232	0.411	0.480	0.363	0.394	0.412
35	0.218	0.857	0.532	0.366	0.390	0.778	0.517	0.441	0.531
36	0.260	0.746	0.949	0.105	0.403	0.663	0.907	0.358	0.583
37	0.366	0.563	0.942	1.000	0.441	0.534	0.896	1.000	0.718
38	0.201	0.880	0.475	0.319	0.385	0.807	0.488	0.424	0.526

39	0.156	0.658	0.975	0.007	0.372	0.594	0.953	0.335	0.564
40	0.360	0.481	0.468	0.404	0.439	0.491	0.484	0.456	0.467

The optimal parametric setting for the system using simulation run is at experiment 16 (Table 2) and the associated values for each factors that were used in computing the various performance indices are shown in Table 3.

Table 3: Optimal parametric settings

Items	Values
Production cost	₦ 138,572,581.00
Cost of spare parts	₦ 180,106.60
Overhead cost	₦ 330,535.27
Workforce cost	₦ 2,556,655.65
Production hours	75 hrs
Breakdown time	15 hrs
Production workers idle time	52.25 %
Maintenance workers idle time	57.40 %
Machine efficiency	66.03 %
Machine utilisation	6.32 %
Machine availability	60.19 %
Machine reliability	86.41 %
Production workers efficiency	77.09 %
Maintenance workers utilisation	95.47 %
Maintenance workers efficiency	75.80 %
Production workers utilisation	56.67 %
Workers turnover rate	0.78 %
Full-time production workers	61 workers
Part-time production workers	33 workers

Note: ₦ 200 = $1

Using the values for $x^*(k)$ and grey relational grade, the information in Table 2, the constants parameters in Equation (2) are generated and the results obtained as depicted in Table 4.

Table 4: Predictive model results

Regression Statistics		Coefficients	
Parameters	Values	Parameters	Values
Multiple R	0.959	Intercept	0.248
R-Square	0.920	y_1	0.137
Adjusted R-square	0.911	y_2	0.124
Standard error (S_e)	0.026	y_3	0.189
No. of observations	40	y_4	0.140

Next, we proceed to the ***design*** of the HOQ for the maintenance-production workforce-based. Based on the authors’ knowledge on maintenance-production systems, and discussions with experts in manufacturing systems, the HOQ for the maintenance-production workforce-based model is presented as Figure 5.

When applying the proposed model, modellers have the final decision on what the interrelationships among the various performance indices and the worker's groups will be. The interpretation of the degree of importance in Figure 5 is that the cost management index is more important than the other performance indices in Figure 5. This is because the level of attainment of other performance indices depends to a large extent on the amount of funds that is made available for their executions. Time management is more important than human and machine performance indices, because manufacturing activities is hinged on how much time is distributed among the various operations in manufacturing systems.

A manufacturing systems with high level of cost and time managements has the potential of generating high value of returns on investment (ROI) from human and machines used during manufacturing activities. However, the ROI from machines is expected to be high when compared with the ROI from workers. This can be seen in the high importance level of machine performance index in Figure 5 when compared with human performance index. The number of full-time production workers that will be used for production tasks only is expected to be approximately 42 % of the total number of maintenance and production workers (Figure 5). The results that will be generated from the optimisation model for the number of full-time maintenance and causal production is expected to be close.

		Degree of importance	Workforce design requirements			
			FTW	CTW	FPMW	CPMW
Management requirements	Machine performance index	23	●	○	●	○
	Human performance index	12	●	○	●	○
	Cost management index	35	●	○	○	○
	Time management index	30	●	●	○	□
Technical Importance	Absolute Importance		900	480	510	240
	Relative Importance		0.42	0.23	0.24	0.11

● Strong interrelationship ○ Medium interrelationship □ Weak interrelationship

Figure 5: HOQ for maintenance-production workers

The information in Table 2 is used in identifying the samples with the minimum and maximum overall performance, and the bounds for the four performance indices used for computing the overall system performance index is fixed objectively. We now proceed to the formulation of the model and solving it using the three selected solution methods. In order to determine the solution boundaries (B), that is the minimum and maximum bounds, statistically, each of the solution methods was run 30 times and Equation (43) is used in computing the bounds for the solutions that were obtained (Engelbrecht, 2007). The results obtained for the 30 different runs using the solution methods are presented in Table 5. At α = 1 %, the performance of the three solution methods are analysed based on Equation (43) and the results obtained as shown in Table 5.

$$B = \overline{\partial} \pm t_{\sim, n-1} \partial \tag{43}$$

$$\partial = \sqrt{\frac{\sum_{i=1}^{n} \left(V_i - \overline{V}\right)^2}{n(n-1)}} \tag{44}$$

Table 5: Performances of the selected solution methods

Runs	BB-BC	PSO	CBO
1	1.443	1.2391	1.4173
2	1.1739	1.8345	1.4102
3	1.2559	1.1343	1.1694
4	1.1038	1.5756	1.1724
5	1.1432	1.2556	1.2278
6	1.2981	1.1323	1.2522
7	1.4393	1.5433	1.2639
8	1.3677	1.5295	1.1359
9	1.5776	1.2607	1.3267
10	1.1701	1.1501	1.2581
11	1.5934	1.6442	1.1235
12	1.434	1.4918	1.3503
13	1.1567	1.3907	1.2984
14	1.3163	1.7291	0.8385
15	1.201	1.2881	1.4653
16	1.4245	1.1824	1.2707
17	1.4151	1.5481	1.1655
18	1.098	1.1849	1.494
19	1.3376	1.6899	1.295
20	1.2383	1.2966	1.2836
21	1.2811	1.3079	1.2773
22	1.1779	1.424	1.1817
23	1.2444	1.3579	1.3193
24	1.0087	1.8762	1.5561
25	1.2916	1.4957	1.0103

26	0.9237	1.0245	1.1308
27	1.2451	1.7607	1.2536
28	1.2392	1.5292	1.3751
29	1.0868	1.4389	1.2797
30	1.135	1.5163	1.3226
Best	0.9237	1.0245	0.8385
Worst	1.5934	1.8762	1.5561
Lower bound	1.1564	1.2782	1.1688
Upper bound	1.3650	1.5773	1.3596

6. Discussion of Results

The current approach used in handling the goals in this paper has been successfully handled and the results obtained for these goals are relatively stable for all the selected solution methods. This approach has the benefit of reducing the dependence on key decision makers in a system associated with using fuzzy goal programming technique (Belmokaddem *et al*., 2014). For instance, there is no need of establishing the limits for an objective to be assigned full or partial membership (fuzzy goal programming) when using Euclidean distance approach. The results presented in Table 5 showed that in terms of the best and the worst solutions, the CBO procedure exhibited better performance than the BB-BC as well as the PSO procedure. Although, the range of solution from the CBO and the BB-BC algorithms are close, a detailed look at the upper bounds of both algorithms indicates that the CBO algorithm results are preferable to the BB-BC algorithm.

Using the CBO algorithm as a solution method in generating the optimal values for the system workforce size, idle time and workloads as well as the expected performance indices were obtained. The optimal value for the single objective function is 1.2470. The optimal value for the total energy efficiency for the system was 0.9750, and the optimal value for the overall system performance and workforce earned-value are 0.5131 and ₦ 7,373,576.54, respectively. The implication of these optimal values on the system performance indices are showed in Table 6. By generating optimal values for these indices, decision makers will be equipped with relevant information on how to manage the available resources (human, machine, time and funds).

Table 6: Optimal values for performance indices

Periods	MPI	HPI	CMI	TMI
1	0.2353	0.3447	0.6019	0.0464
2	0.2662	0.3589	0.7635	0.1124
3	0.3199	0.8256	0.5043	0.4596
4	0.2086	0.5280	0.7279	0.7084

Based on the optimal values in Table 6, the cost management index for the system is higher across all the periods. The total value for the overall system performance (i.e., objective function 2), that is 51.31%, can be attributed to the low optimal values for the different performance indices in Table 6. The deviation of the optimal value obtained for the second objective from the minimum and maximum values in Table 2 are 0.1040 and

0.2690, respectively. This shows that the proposed model was able to establish a compromise between the grey relational grade's minimum and maximum values. The optimal results can be seen as being flexible when compared with the grey relational grade in Table 2. By equipping decision makers with this information, an improved instruction can be communicated to workers on how the organisation's goals (human, time, machine and funds management) can be achievable. The optimal distribution of workforce that is associated with the above performance indices is showed in Table 7.

Table 7: Optimal values for workforce idle time, size and workloads

	Group 1			Group 2		
Periods (Months)	Idle time (hr)	Workforce size	Workload (hr)	Idle time (hr)	Workforce size	Workload (hr)
	Production variables					
1	0.5868	70	8.3643	0.5822	34	8.461
2	0.4834	66	9.6993	0.7851	36	6.8160
3	0.6229	63	8.3824	0.8575	33	8.0833
4	0.5699	64	6.8880	0.8581	31	8.8667
	Maintenance-production variables					
	Group 1			Group 2		
1	0.6808	25	1.1226	1.0303	13	1.0131
2	1.025	23	0.7290	0.4712	14	1.3881
3	0.9174	29	1.4197	0.9892	14	1.1957
4	0.8504	19	1.0150	0.6139	11	0.5097

From the results in Table 7, the amount of idle time that is allocated to the scheduled maintenance-production workers is higher than the amount of idle time allocated to the scheduled production workers by approximately 18.7%. In practice, this result is expected especially for systems with low level of automation.

The results for workforce size showed that the number of workers in group 1 is approximately twice the total number of workers in group 2. This result is consistent with the ratio of relative importance workforce in Figure 5. Thus, it may be inferred that with QFD, the relationships among the different workers' group can be used to establish an inexact workforce plan under different management requirements for a new manufacturing systems when there is insufficient data for the implementation of workforce optimisation models. Also, the QFD framework will help in providing a platform upon which simulation of the effect of variation in the relative importance of different management requirements will have on the workforce structure.

The main implications of the workforce structure in Table 7 are in four phases. In the first (cost implication) phase, during workforce planning, the quantum of funds that will be budgeted for workforce expenses can be tracked easily. For instance, more funds will be required to take care of for the workforce at period 1 than any other period. Period 4 requires the least amount of funds for workforce expenses. This information will help in improving funds budgeting. The second phase deals with the benefit of time management. To effectively manage the available manufacturing time, decision makers are interested in the proportion of time required to be contributed by each group of workers towards the organisational goals. The optimal values for time allocated for the full-time (groups 1) and causal (groups 2) workers showed that the full-time workers require more time than causal workers (approximately 3.5 %). This showed that the distribution of the available manufacturing time should be at a ratio of 56.5: 43.5 % for groups 1 and 2, respectively.

This information will aid decision makers in generating an approximate time utilisation plan for the workers. By and large, bias towards allocating more time to a certain group of workers will be reduced to the bearable limits. This will translate to harmonious working relationships among the different groups of workers in manufacturing systems and improve the attainment of organisation goals.

The third phase deals with machine performance management. The issue of labour shortage when there is urgent demand for a company service can be properly handled given the time requirement for such service. With the time requirement for a particular service, the number of maintenance-production and production workers that should be scheduled can be easily determined. This will help in improving the utilisation of machines in the system. Also, the problem of delay in production activities as a result of labour shortages, especially for a system that does not have a separate maintenance and production departments, can be handled with the proposed model. For instance, a minimum of 30 workers will be needed in scheduling, to implement maintenance-production activities at any point in time. Under this case, 19 and 11 workers will be required from worker's groups 1 and 2, respectively.

Lastly (human performance), provision of idle time in the design of workforce structure is necessary, despite the calculated periods for breaks. Such idle time may be the time due to emergency breakdown, delay in releasing materials for production or maintenance activities, delay in receiving instruction from supervisors and other unquantifiable human factors in production systems (fatigue). In the system, the minimum amounts of idle time for maintenance-production and production workers are 1.464 and 1.169 hr, respectively. In summary, the information in Table 7 will complement existing tools used in the design of motivation scheme for workers who carry out maintenance-production and production activities.

The results obtained from the proposed model are data sensitive. There is a possibility of obtaining a different set of results if some of the parameters used in testing the proposed model are changed. Furthermore, in a production system where there are separate production and maintenance workforce (department), that is a system where the maintenance and production workers are only allowed to perform a specific task, the proposed model is still applicable. For such systems, the amounts of production workloads in Equations (1), (14), (15), and (19) will have to be modified so as to accurately account for the total time used for maintenance activities. In explicit terms, all workloads and idle times that are attributed to maintenance workers that will engage in production activities becomes zero.

7. Conclusions

The determination of effective workforce size for manufacturing systems has been a long-standing problem in the operations and maintenance arena. The problem becomes more important when considering the amalgamation of maintenance and production functions, which will be carried out by only one set of technical personnel. Several efforts have been expended to improve the accuracy of prediction, and evaluation on determination of the workforce size in manufacturing. However, most effort had been concentrated on production workforce determination alone and a handful of recent investigations are directed at maintenance function workforce determination.

Unfortunately, the literature search results did not produce any realistic detailed analysis of the integrated maintenance and production workforce determination, opening a gap for further enquires on the possible conceptualisation of such a useful integration. The investigation reported in this article has made conscious advancement in the analysis of workforce that would perform integrated functions in both maintenance and production functions. This investigation considers the development of an approach, based on the marriage of fuzzy logic and QFD concepts for capturing uncertainty in workforce analysis for manufacturing systems. A further attempt was made to produce optimal workforce size by utilising CBO algorithm. The results obtained were compared with that of the BB-BC and PSO algorithms. We observed that the BB-BC algorithm results were closed to that of the CBO algorithm results.

The implementation of the proposed model using practical data showed that the model is easy to implement and practicable. The QFD framework presented has been able to show that the integration of management and workforce requirements can be used as a tool for planning the performance to expect from factors used in manufacturing activities when combined with optimisation model. However, the current QFD can be extended to incorporate the contributions of non-engineering workers in manufacturing systems.

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APPENDIX A

Section A

1. What is the number of products produced?

2. What is the average weekly production volume of each product?

Product A	Product B	Product C	Product D	Product E

3. Do your company outsource production activity?
4. If yes, what is the average weekly volume of each product that is outsourced?

Product A	Product B	Product C	Product D	Product E

5. What is the unit cost of outsourced product?

Product A	Product B	Product C	Product D	Product E

Section B

In this section, information on evaluation of the performance of a production system is required. The set of selected questions are presented below, while the rating system for these questions is given as follows:

Grade	Interpretation
Low	Less than 40 %
Medium	41-60 %
High	60- 80 %
Very high	Above 80 %

Sn	Questions for responses	Low	Medium	High	Very high
1	How will you rate production workers idle time in your company?				
2	How will you rate maintenance workers idle time in your company?				
3	How will you rate machine efficiency in your company?				
4	How will you rate machine utilisation in your company?				
5	How will you rate machine availability in your company?				
6	How will you rate machine reliability in your company?				
7	How will you rate production workers efficiency in your company?				
8	How will you rate maintenance workers utilisation in your company?				
9	How will you rate maintenance workers efficiency in your company?				
10	How will you rate production workers utilisation in your company?				
11	How will you rate workers turnover rate in your company?				

Section C

In this section, the range of some resources used during weekly production activities is required. Kindly assist us in providing information for the following set of questions:

S/No.	Questions for responses	

1	What is the range of weekly full-time production workers?	
2	What is the range of weekly full-time maintenance workers?	
3	What is the range of weekly causal production workers?	
4	What is the range of weekly causal maintenance workers?	
5	What is the range weekly production?	
6	What is the range of weekly breakdown time?	
7	What is the range of weekly production cost?	
8	What is the range of weekly maintenance cost?	
9	What is the range of weekly cost of spare cost?	
10	What is the range of weekly workforce cost/?	
12	What is the range of weekly maintenance?	
13	What is the range of weekly production time?	